

```
In [2]: import numpy as np
import pandas as pd
import warnings

warnings.filterwarnings('ignore')

# Generating synthetic data
np.random.seed(0)
data_size = 200
features = np.random.rand(data_size, 2) # Two features: visit duration and
labels = (features[:, 0] + features[:, 1] > 1).astype(int) # Purchase (1) c

# Convert to DataFrame for easier manipulation
df = pd.DataFrame(features, columns=['VisitDuration', 'PagesVisited'])
df['Purchase'] = labels

# Print the 'features' array
print("--- Features Array (NumPy) ---")
print(features)
print("\nShape of features array:", features.shape)
print("Type of features array:", type(features))

# Print the 'df' DataFrame
print("\n--- DataFrame (Pandas) ---")
print(df)
print("\nShape of DataFrame:", df.shape)
print("Type of DataFrame:", type(df))
print("\nInfo of DataFrame:")
df.info()
print("\nHead of DataFrame:")
print(df.head())
print("\nTail of DataFrame:")
print(df.tail())
```

--- Features Array (NumPy) ---

```
[0.5488135  0.71518937]
[0.60276338 0.54488318]
[0.4236548  0.64589411]
[0.43758721 0.891773  ]
[0.96366276 0.38344152]
[0.79172504 0.52889492]
[0.56804456 0.92559664]
[0.07103606 0.0871293  ]
[0.0202184  0.83261985]
[0.77815675 0.87001215]
[0.97861834 0.79915856]
[0.46147936 0.78052918]
[0.11827443 0.63992102]
[0.14335329 0.94466892]
[0.52184832 0.41466194]
[0.26455561 0.77423369]
[0.45615033 0.56843395]
[0.0187898  0.6176355  ]
[0.61209572 0.616934  ]
[0.94374808 0.6818203  ]
[0.3595079  0.43703195]
[0.6976312  0.06022547]
[0.66676672 0.67063787]
[0.21038256 0.1289263  ]
[0.31542835 0.36371077]
[0.57019677 0.43860151]
[0.98837384 0.10204481]
[0.20887676 0.16130952]
[0.65310833 0.2532916  ]
[0.46631077 0.24442559]
[0.15896958 0.11037514]
[0.65632959 0.13818295]
[0.19658236 0.36872517]
[0.82099323 0.09710128]
[0.83794491 0.09609841]
[0.97645947 0.4686512  ]
[0.97676109 0.60484552]
[0.73926358 0.03918779]
[0.28280696 0.12019656]
[0.2961402  0.11872772]
[0.31798318 0.41426299]
[0.0641475  0.69247212]
[0.56660145 0.26538949]
[0.52324805 0.09394051]
[0.5759465  0.9292962  ]
[0.31856895 0.66741038]
[0.13179786 0.7163272  ]
[0.28940609 0.18319136]
[0.58651293 0.02010755]
[0.82894003 0.00469548]
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[0.73519402 0.96218855]
[0.24875314 0.57615733]
[0.59204193 0.57225191]
[0.22308163 0.95274901]
```

[0.44712538 0.84640867]
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[0.95608363 0.6439902]
[0.42385505 0.60639321]
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[0.8965466 0.36756187]
[0.43586493 0.89192336]
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[0.10022689 0.91948261]
[0.7142413 0.99884701]
[0.1494483 0.86812606]
[0.16249293 0.61555956]
[0.12381998 0.84800823]
[0.80731896 0.56910074]
[0.4071833 0.069167]
[0.69742877 0.45354268]
[0.7220556 0.86638233]
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[0.01171408 0.35997806]
[0.72999056 0.17162968]
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[0.19999652 0.01852179]
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[0.7044144 0.03183893]
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[0.57722859 0.23789282]
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[0.5356328 0.58990998]
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[0.020651 0.75837865]
[0.32001715 0.38346389]
[0.58831711 0.83104846]
[0.62898184 0.87265066]

[0.27354203 0.79804683]
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[0.68748828 0.21550768]
[0.94737059 0.73085581]
[0.25394164 0.21331198]
[0.51820071 0.02566272]
[0.20747008 0.42468547]
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[0.27762871 0.58678435]
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[0.35561274 0.94043195]
[0.76532525 0.74866362]
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[0.24082878 0.10029394]
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[0.33815895 0.96157015]
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[0.63044794 0.87428797]
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[0.33314515 0.08110139]
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[0.72559436 0.01142746]
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[0.42053947 0.55736879]
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[0.26211815 0.45614057]
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[0.28351885 0.37992696]
[0.18115096 0.78854551]
[0.05684808 0.69699724]

```
[0.7786954  0.77740756]
[0.25942256 0.37381314]
[0.58759964 0.2728219 ]
[0.3708528  0.19705428]
[0.45985588 0.0446123 ]
[0.79979588 0.07695645]
[0.51883515 0.3068101 ]
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[0.53617749 0.68139251]
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[0.18713089 0.90398395]
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[0.88204141 0.45860396]
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[0.90404439 0.69002502]
[0.69962205 0.3277204 ]
[0.75677864 0.63606106]
[0.24002027 0.16053882]
[0.79639147 0.9591666 ]
[0.45813883 0.59098417]
[0.85772264 0.45722345]
[0.95187448 0.57575116]
[0.82076712 0.90884372]
[0.81552382 0.15941446]
[0.62889844 0.39843426]
[0.06271295 0.42403225]
[0.25868407 0.84903831]
[0.03330463 0.95898272]
[0.35536885 0.35670689]
[0.0163285  0.18523233]]
```

```
Shape of features array: (200, 2)
Type of features array: <class 'numpy.ndarray'>
```

```
--- DataFrame (Pandas) ---
   VisitDuration  PagesVisited  Purchase
0         0.548814         0.715189         1
1         0.602763         0.544883         1
2         0.423655         0.645894         1
3         0.437587         0.891773         1
4         0.963663         0.383442         1
..          ...          ...          ...
195        0.062713         0.424032         0
196        0.258684         0.849038         1
197        0.033305         0.958983         0
198        0.355369         0.356707         0
199        0.016329         0.185232         0
```

```
[200 rows x 3 columns]
```

```
Shape of DataFrame: (200, 3)
Type of DataFrame: <class 'pandas.core.frame.DataFrame'>
```

Info of DataFrame:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 3 columns):
#   Column          Non-Null Count  Dtype
---  -
0   VisitDuration    200 non-null    float64
1   PagesVisited     200 non-null    float64
2   Purchase         200 non-null    int64
dtypes: float64(2), int64(1)
memory usage: 4.8 KB
```

Head of DataFrame:

	VisitDuration	PagesVisited	Purchase
0	0.548814	0.715189	1
1	0.602763	0.544883	1
2	0.423655	0.645894	1
3	0.437587	0.891773	1
4	0.963663	0.383442	1

Tail of DataFrame:

	VisitDuration	PagesVisited	Purchase
195	0.062713	0.424032	0
196	0.258684	0.849038	1
197	0.033305	0.958983	0
198	0.355369	0.356707	0
199	0.016329	0.185232	0

```
In [4]: from sklearn.model_selection import train_test_split

# Split the data
X_train, X_test, y_train, y_test = train_test_split(df[['VisitDuration', 'Pa
```

```
In [16]: import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Define the model
model = Sequential([
    Dense(10, activation='relu', input_shape=(2,)), # Input layer with 2 fe
    Dense(1, activation='sigmoid') # Output layer with sigmoid activation f
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accura

# Suppress Warnings
import warnings
warnings.filterwarnings('ignore')

# Train the model and save the history
history = model.fit(X_train, y_train, epochs=100, batch_size=5, validation_s




















# Plotting training and validation loss and accuracy
import matplotlib.pyplot as plt
```



















```
plt.figure(figsize=(12, 5))

# Plot training & validation accuracy values
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

plt.show()
```

Epoch 1/100
26/26  **1s** 14ms/step - accuracy: 0.4228 - loss: 0.7097 - val_accuracy: 0.4688 - val_loss: 0.7068
Epoch 2/100
26/26  **0s** 6ms/step - accuracy: 0.5021 - loss: 0.6910 - val_accuracy: 0.4688 - val_loss: 0.7001
Epoch 3/100
26/26  **0s** 6ms/step - accuracy: 0.5184 - loss: 0.6904 - val_accuracy: 0.5000 - val_loss: 0.6932
Epoch 4/100
26/26  **0s** 5ms/step - accuracy: 0.5974 - loss: 0.6846 - val_accuracy: 0.5312 - val_loss: 0.6872
Epoch 5/100
26/26  **0s** 6ms/step - accuracy: 0.6526 - loss: 0.6761 - val_accuracy: 0.5938 - val_loss: 0.6806
Epoch 6/100
26/26  **0s** 6ms/step - accuracy: 0.6995 - loss: 0.6601 - val_accuracy: 0.6250 - val_loss: 0.6752
Epoch 7/100
26/26  **0s** 6ms/step - accuracy: 0.6589 - loss: 0.6675 - val_accuracy: 0.6250 - val_loss: 0.6691
Epoch 8/100
26/26  **0s** 5ms/step - accuracy: 0.7045 - loss: 0.6606 - val_accuracy: 0.6875 - val_loss: 0.6633
Epoch 9/100
26/26  **0s** 6ms/step - accuracy: 0.6458 - loss: 0.6708 - val_accuracy: 0.6875 - val_loss: 0.6567
Epoch 10/100
26/26  **0s** 6ms/step - accuracy: 0.7142 - loss: 0.6530 - val_accuracy: 0.7188 - val_loss: 0.6515
Epoch 11/100
26/26  **0s** 5ms/step - accuracy: 0.7331 - loss: 0.6531 - val_accuracy: 0.6875 - val_loss: 0.6448
Epoch 12/100
26/26  **0s** 5ms/step - accuracy: 0.7716 - loss: 0.6419 - val_accuracy: 0.6875 - val_loss: 0.6390
Epoch 13/100
26/26  **0s** 5ms/step - accuracy: 0.7864 - loss: 0.6410 - val_accuracy: 0.7188 - val_loss: 0.6332
Epoch 14/100
26/26  **0s** 5ms/step - accuracy: 0.7321 - loss: 0.6506 - val_accuracy: 0.7188 - val_loss: 0.6276
Epoch 15/100
26/26  **0s** 5ms/step - accuracy: 0.8160 - loss: 0.6244 - val_accuracy: 0.6875 - val_loss: 0.6205
Epoch 16/100
26/26  **0s** 6ms/step - accuracy: 0.7979 - loss: 0.6307 - val_accuracy: 0.7500 - val_loss: 0.6147
Epoch 17/100
26/26  **0s** 6ms/step - accuracy: 0.8115 - loss: 0.6137 - val_accuracy: 0.7188 - val_loss: 0.6077
Epoch 18/100
26/26  **0s** 5ms/step - accuracy: 0.8515 - loss: 0.6100 - val_accuracy: 0.7500 - val_loss: 0.6016
Epoch 19/100
26/26  **0s** 5ms/step - accuracy: 0.8644 - loss: 0.5901 - va

l_accuracy: 0.8125 - val_loss: 0.5961
Epoch 20/100
26/26  **0s** 6ms/step - accuracy: 0.8069 - loss: 0.6049 - va
l_accuracy: 0.8125 - val_loss: 0.5890
Epoch 21/100
26/26  **0s** 6ms/step - accuracy: 0.8287 - loss: 0.5939 - va
l_accuracy: 0.8125 - val_loss: 0.5815
Epoch 22/100
26/26  **0s** 6ms/step - accuracy: 0.7835 - loss: 0.6001 - va
l_accuracy: 0.8125 - val_loss: 0.5753
Epoch 23/100
26/26  **0s** 6ms/step - accuracy: 0.8466 - loss: 0.5873 - va
l_accuracy: 0.8125 - val_loss: 0.5685
Epoch 24/100
26/26  **0s** 6ms/step - accuracy: 0.8285 - loss: 0.5840 - va
l_accuracy: 0.8125 - val_loss: 0.5619
Epoch 25/100
26/26  **0s** 5ms/step - accuracy: 0.8488 - loss: 0.5550 - va
l_accuracy: 0.8125 - val_loss: 0.5546
Epoch 26/100
26/26  **0s** 6ms/step - accuracy: 0.8318 - loss: 0.5608 - va
l_accuracy: 0.8125 - val_loss: 0.5476
Epoch 27/100
26/26  **0s** 6ms/step - accuracy: 0.7919 - loss: 0.5701 - va
l_accuracy: 0.8438 - val_loss: 0.5411
Epoch 28/100
26/26  **0s** 5ms/step - accuracy: 0.8480 - loss: 0.5554 - va
l_accuracy: 0.8125 - val_loss: 0.5340
Epoch 29/100
26/26  **0s** 5ms/step - accuracy: 0.8715 - loss: 0.5460 - va
l_accuracy: 0.8438 - val_loss: 0.5271
Epoch 30/100
26/26  **0s** 5ms/step - accuracy: 0.8458 - loss: 0.5348 - va
l_accuracy: 0.8750 - val_loss: 0.5202
Epoch 31/100
26/26  **0s** 5ms/step - accuracy: 0.8598 - loss: 0.5479 - va
l_accuracy: 0.8750 - val_loss: 0.5130
Epoch 32/100
26/26  **0s** 5ms/step - accuracy: 0.8921 - loss: 0.5433 - va
l_accuracy: 0.8750 - val_loss: 0.5059
Epoch 33/100
26/26  **0s** 6ms/step - accuracy: 0.8881 - loss: 0.5259 - va
l_accuracy: 0.8750 - val_loss: 0.4976
Epoch 34/100
26/26  **0s** 5ms/step - accuracy: 0.8511 - loss: 0.5365 - va
l_accuracy: 0.8750 - val_loss: 0.4907
Epoch 35/100
26/26  **0s** 5ms/step - accuracy: 0.8725 - loss: 0.5286 - va
l_accuracy: 0.8750 - val_loss: 0.4828
Epoch 36/100
26/26  **0s** 5ms/step - accuracy: 0.8795 - loss: 0.5085 - va
l_accuracy: 0.8750 - val_loss: 0.4749
Epoch 37/100
26/26  **0s** 5ms/step - accuracy: 0.9206 - loss: 0.4931 - va
l_accuracy: 0.8750 - val_loss: 0.4673
Epoch 38/100

26/26 ————— 0s 5ms/step - accuracy: 0.9340 - loss: 0.4986 - val_accuracy: 0.8750 - val_loss: 0.4595
Epoch 39/100

26/26 ————— 0s 5ms/step - accuracy: 0.9238 - loss: 0.4738 - val_accuracy: 0.8750 - val_loss: 0.4518
Epoch 40/100

26/26 ————— 0s 5ms/step - accuracy: 0.9011 - loss: 0.4752 - val_accuracy: 0.8750 - val_loss: 0.4441
Epoch 41/100

26/26 ————— 0s 5ms/step - accuracy: 0.8759 - loss: 0.4686 - val_accuracy: 0.8750 - val_loss: 0.4368
Epoch 42/100

26/26 ————— 0s 5ms/step - accuracy: 0.9245 - loss: 0.4668 - val_accuracy: 0.8750 - val_loss: 0.4287
Epoch 43/100

26/26 ————— 0s 5ms/step - accuracy: 0.9240 - loss: 0.4471 - val_accuracy: 0.8750 - val_loss: 0.4212
Epoch 44/100

26/26 ————— 0s 5ms/step - accuracy: 0.9179 - loss: 0.4698 - val_accuracy: 0.9688 - val_loss: 0.4137
Epoch 45/100

26/26 ————— 0s 5ms/step - accuracy: 0.9128 - loss: 0.4496 - val_accuracy: 0.9688 - val_loss: 0.4068
Epoch 46/100

26/26 ————— 0s 5ms/step - accuracy: 0.9153 - loss: 0.4539 - val_accuracy: 0.9062 - val_loss: 0.3994
Epoch 47/100

26/26 ————— 0s 5ms/step - accuracy: 0.9759 - loss: 0.4187 - val_accuracy: 0.9688 - val_loss: 0.3923
Epoch 48/100

26/26 ————— 0s 5ms/step - accuracy: 0.9526 - loss: 0.4264 - val_accuracy: 0.9688 - val_loss: 0.3856
Epoch 49/100

26/26 ————— 0s 5ms/step - accuracy: 0.9646 - loss: 0.4156 - val_accuracy: 0.9688 - val_loss: 0.3787
Epoch 50/100

26/26 ————— 0s 5ms/step - accuracy: 0.9556 - loss: 0.4065 - val_accuracy: 1.0000 - val_loss: 0.3723
Epoch 51/100

26/26 ————— 0s 5ms/step - accuracy: 0.9612 - loss: 0.4084 - val_accuracy: 0.9688 - val_loss: 0.3657
Epoch 52/100




















26/26 ————— 0s 5ms/step - accuracy: 0.9666 - loss: 0.4058 - val_accuracy: 1.0000 - val_loss: 0.3597
Epoch 53/100













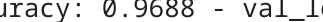
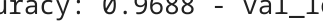




26/26 ————— 0s 5ms/step - accuracy: 0.9701 - loss: 0.3912 - val_accuracy: 1.0000 - val_loss: 0.3531
Epoch 54/100

26/26 ————— 0s 5ms/step - accuracy: 0.9824 - loss: 0.3910 - val_accuracy: 1.0000 - val_loss: 0.3471
Epoch 55/100

26/26 ————— 0s 5ms/step - accuracy: 0.9652 - loss: 0.3872 - val_accuracy: 1.0000 - val_loss: 0.3416
Epoch 56/100

26/26 ————— 0s 5ms/step - accuracy: 0.9427 - loss: 0.3824 - val_accuracy: 1.0000 - val_loss: 0.3361

Epoch 57/100
26/26  **0s** 5ms/step - accuracy: 0.9789 - loss: 0.3604 - val_accuracy: 1.0000 - val_loss: 0.3306
Epoch 58/100
26/26  **0s** 5ms/step - accuracy: 0.9917 - loss: 0.3550 - val_accuracy: 1.0000 - val_loss: 0.3252
Epoch 59/100
26/26  **0s** 5ms/step - accuracy: 0.9417 - loss: 0.3670 - val_accuracy: 1.0000 - val_loss: 0.3202
Epoch 60/100
26/26  **0s** 5ms/step - accuracy: 0.9478 - loss: 0.3689 - val_accuracy: 1.0000 - val_loss: 0.3150
Epoch 61/100
26/26  **0s** 5ms/step - accuracy: 0.9710 - loss: 0.3648 - val_accuracy: 1.0000 - val_loss: 0.3099
Epoch 62/100
26/26  **0s** 5ms/step - accuracy: 0.9699 - loss: 0.3520 - val_accuracy: 1.0000 - val_loss: 0.3053
Epoch 63/100
26/26  **0s** 5ms/step - accuracy: 0.9691 - loss: 0.3717 - val_accuracy: 1.0000 - val_loss: 0.3009
Epoch 64/100
26/26  **0s** 5ms/step - accuracy: 0.9799 - loss: 0.3383 - val_accuracy: 0.9688 - val_loss: 0.2964
Epoch 65/100
26/26  **0s** 5ms/step - accuracy: 0.9799 - loss: 0.3429 - val_accuracy: 1.0000 - val_loss: 0.2920
Epoch 66/100
26/26  **0s** 5ms/step - accuracy: 0.9628 - loss: 0.3715 - val_accuracy: 1.0000 - val_loss: 0.2876
Epoch 67/100
26/26  **0s** 5ms/step - accuracy: 0.9510 - loss: 0.3186 - val_accuracy: 1.0000 - val_loss: 0.2834
Epoch 68/100
26/26  **0s** 5ms/step - accuracy: 0.9535 - loss: 0.3646 - val_accuracy: 1.0000 - val_loss: 0.2797
Epoch 69/100
26/26  **0s** 5ms/step - accuracy: 0.9925 - loss: 0.3054 - val_accuracy: 1.0000 - val_loss: 0.2754
Epoch 70/100
26/26  **0s** 6ms/step - accuracy: 0.9379 - loss: 0.3195 - val_accuracy: 0.9688 - val_loss: 0.2721
Epoch 71/100
26/26  **0s** 5ms/step - accuracy: 0.9810 - loss: 0.2985 - val_accuracy: 0.9688 - val_loss: 0.2678
Epoch 72/100
26/26  **0s** 5ms/step - accuracy: 0.9636 - loss: 0.3114 - val_accuracy: 0.9688 - val_loss: 0.2645
Epoch 73/100
26/26  **0s** 5ms/step - accuracy: 0.9661 - loss: 0.2895 - val_accuracy: 0.9688 - val_loss: 0.2608
Epoch 74/100
26/26  **0s** 5ms/step - accuracy: 0.9757 - loss: 0.3078 - val_accuracy: 0.9688 - val_loss: 0.2576
Epoch 75/100
26/26  **0s** 5ms/step - accuracy: 0.9929 - loss: 0.2695 - va

l_accuracy: 0.9688 - val_loss: 0.2539
Epoch 76/100
26/26  **0s** 5ms/step - accuracy: 0.9858 - loss: 0.2837 - va
l_accuracy: 0.9688 - val_loss: 0.2506
Epoch 77/100
26/26  **0s** 5ms/step - accuracy: 0.9651 - loss: 0.2917 - va
l_accuracy: 0.9688 - val_loss: 0.2476
Epoch 78/100
26/26  **0s** 5ms/step - accuracy: 0.9645 - loss: 0.2860 - va
l_accuracy: 0.9688 - val_loss: 0.2446
Epoch 79/100
26/26  **0s** 5ms/step - accuracy: 0.9597 - loss: 0.2807 - va
l_accuracy: 0.9688 - val_loss: 0.2414
Epoch 80/100
26/26  **0s** 5ms/step - accuracy: 0.9485 - loss: 0.2869 - va
l_accuracy: 0.9688 - val_loss: 0.2386
Epoch 81/100
26/26  **0s** 5ms/step - accuracy: 0.9819 - loss: 0.2797 - va
l_accuracy: 1.0000 - val_loss: 0.2357
Epoch 82/100
26/26  **0s** 5ms/step - accuracy: 0.9723 - loss: 0.2734 - va
l_accuracy: 0.9688 - val_loss: 0.2330
Epoch 83/100
26/26  **0s** 6ms/step - accuracy: 0.9524 - loss: 0.2744 - va
l_accuracy: 0.9688 - val_loss: 0.2302
Epoch 84/100
26/26  **0s** 5ms/step - accuracy: 0.9555 - loss: 0.2639 - va
l_accuracy: 0.9688 - val_loss: 0.2276
Epoch 85/100
26/26  **0s** 5ms/step - accuracy: 0.9648 - loss: 0.2763 - va
l_accuracy: 0.9688 - val_loss: 0.2249
Epoch 86/100
26/26  **0s** 5ms/step - accuracy: 0.9601 - loss: 0.2556 - va
l_accuracy: 0.9688 - val_loss: 0.2227
Epoch 87/100
26/26  **0s** 6ms/step - accuracy: 0.9561 - loss: 0.2864 - va
l_accuracy: 0.9688 - val_loss: 0.2201
Epoch 88/100
26/26  **0s** 6ms/step - accuracy: 0.9676 - loss: 0.2718 - va
l_accuracy: 0.9688 - val_loss: 0.2178
Epoch 89/100
26/26  **0s** 5ms/step - accuracy: 0.9853 - loss: 0.2702 - va
l_accuracy: 0.9688 - val_loss: 0.2152
Epoch 90/100
26/26  **0s** 5ms/step - accuracy: 0.9684 - loss: 0.2467 - va
l_accuracy: 0.9688 - val_loss: 0.2130
Epoch 91/100
26/26  **0s** 6ms/step - accuracy: 0.9778 - loss: 0.2464 - va
l_accuracy: 0.9688 - val_loss: 0.2107
Epoch 92/100
26/26  **0s** 6ms/step - accuracy: 0.9413 - loss: 0.2864 - va
l_accuracy: 1.0000 - val_loss: 0.2089
Epoch 93/100
26/26  **0s** 6ms/step - accuracy: 0.9560 - loss: 0.2534 - va
l_accuracy: 0.9688 - val_loss: 0.2066
Epoch 94/100

26/26 ————— 0s 6ms/step - accuracy: 0.9899 - loss: 0.2281 - val_accuracy: 0.9688 - val_loss: 0.2043
Epoch 95/100

26/26 ————— 0s 5ms/step - accuracy: 0.9790 - loss: 0.2548 - val_accuracy: 0.9688 - val_loss: 0.2023
Epoch 96/100

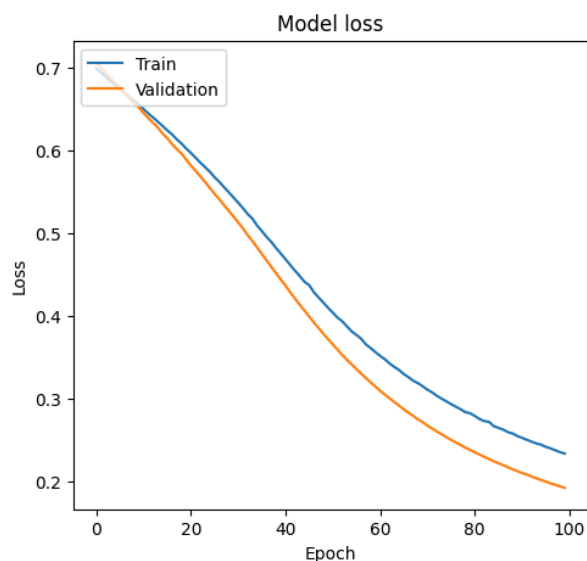
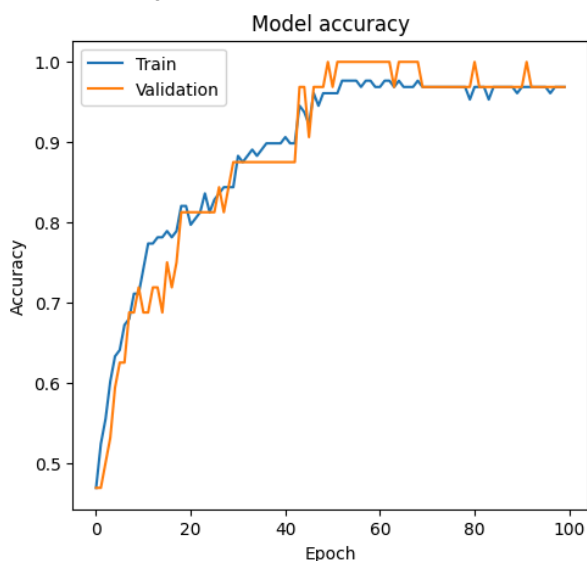
26/26 ————— 0s 5ms/step - accuracy: 0.9555 - loss: 0.2629 - val_accuracy: 0.9688 - val_loss: 0.2004
Epoch 97/100

26/26 ————— 0s 5ms/step - accuracy: 0.9683 - loss: 0.2434 - val_accuracy: 0.9688 - val_loss: 0.1983
Epoch 98/100

26/26 ————— 0s 5ms/step - accuracy: 0.9598 - loss: 0.2199 - val_accuracy: 0.9688 - val_loss: 0.1966
Epoch 99/100

26/26 ————— 0s 6ms/step - accuracy: 0.9669 - loss: 0.2233 - val_accuracy: 0.9688 - val_loss: 0.1947
Epoch 100/100

26/26 ————— 0s 5ms/step - accuracy: 0.9765 - loss: 0.2298 - val_accuracy: 0.9688 - val_loss: 0.1929



```
In [17]: # Evaluate the model on the test set
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {accuracy}")
```

2/2 ————— 0s 29ms/step - accuracy: 0.9187 - loss: 0.2645
Test Accuracy: 0.925000011920929